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# Peer Effects in Climate Change Beliefs

Changes in rainfall and temperatures as well as more frequent and severer natural disasters resulting from climate change have led to significant social and economic costs (Auffhammer (2018); Kousky (2014)). A wide climate change consensus will facilitate collective actions to adapt to climate changes and mitigate losses of environmental and ecosystem deterioration. However, there are vast variations in beliefs about climate change in the United States. Only about half of Americans view climate change as a personal risk (Ballew et al. (2019)). Providing an understanding of climate change belief formation is a crucial contribution to developing positive economic behaviors. Peer groups could serve as important information transmission networks or be influential in changing social norms (Dahl et al. (2014)). For this reason, our paper hypothesizes that peers play an important role in climate change belief formations and identifies the key opinion leaders and policy injection points.

Spatial autoregressive model (SAR) is a classic peer effects model. We study the impact of peers' beliefs on climate change belief formation, conditional on peers' and own socioeconomic conditions and county fixed effects by using SAR model. The estimation equation is as follows:

$$y_{it} = \lambda W y_{it} + \beta X_{it} + \gamma W X_{it} + \mu_i + \mu_t + \epsilon_{it} \quad (1)$$

Climate change beliefs  $y_{it}$  in county  $i$  and year  $t$  are from Yale Climate Change Communication Survey of 2014, 2016, 2018 and 2020. They are measured by the percentage of survey participants in a county that agree with the statements (1=agree, 0=disagree): (1) Global warming is happening, (2) Global warming is caused mostly by human activities, (3) Global warming is affecting the weather in the United States; or (1=yes, 0=no) (4) Whether respondents worry about global warming, (5) Whether respondents are concerned about global warming effects on people.

Our method contributes to the existing literature on peer effects by introducing peer networks at the county level. We define network weighting matrices  $W$  based on the geographic neighboring relation and disparities in the Facebook Social Connectedness Index (SCI) (Bailey et al. (2018)). Each element  $w_{ij}$  in weighting matrix  $W$  measures the closeness in one of the peer networks between county  $i$  and its peer county  $j$ . For a county pair  $w_{ij}$ , geographic peer network is measured by a contiguity spatial weighting matrix; SCI is constructed as the number of friendship connections between the two counties divided by the product of the total number of users in each county. Facebook social matrix defines peer relationships based on the differences in the values of SCI. The matrices are row standardized to gauge the relative importance of each peer county.

A vector of control variables  $X$ , which may be correlated with climate change beliefs, includes residents' demographic information and weather-related variables at the county level. The demographic variables include income, age, education, and race, which are sourced from the ACS 5-year average for each wave of the belief data. The impact of weather disasters is captured by fire, flood, hurricane, storm, and tornado in 2013, 2015, 2017, and 2019 from the Federal Emergency Management Agency (FEMA). We consider a lag belief effect of the disasters by considering the disasters that took place within one year prior to our survey waves. Peer effects are captured by the coefficient on the average peer beliefs in climate change  $W y$ .  $W X$  are peers' average characteristics. The variable  $\mu_i$  and  $\mu_t$  captures county and time fixed effects, and  $\epsilon_{it}$  is the error term. Following Bramoullé et al. (2009), we use peers' average characteristics  $W^2 X$  as instruments for endogenous peer effects from  $W y$ .

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We find significantly positive peer effects defined based on geographic and SCI networks. A 1% increase in the peer counties' proportion of people who believe in climate change is associated with 0.61%-0.94% increase in own county's proportion of people who believe in climate change, depending on the measurements of beliefs in climate change. We speculate that peer effects through geographic and Facebook networks may come from information sharing. People living closer to each other or are friends on Facebook are more likely to share information with each other and thus have a strong influence on their peers' climate change beliefs.

Our results show significant peer effects in climate change beliefs, and the importance of peers in determining climate change beliefs. Our future work will include networks combination peer effects in the regression to distinguish the importance of each peer network. Following [Banerjee et al. \(2013\)](#), we will identify the key opinion leaders and policy injection points in these peer networks, and understand where, and in what ways, peer effects are most effective in changing beliefs in climate change.

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